Business Experimentation and Causal Methods

Prof. Fradkin
Topic: Non-Compliance

This Time

1. **Why not everyone might get the treatment.**
2. Intent to treat effect and the complier average causal effect.
3. Voter turnout example + Placebos.

Definition of non-compliance:

Some people assigned to the treatment do not get it. (Focus on this one today)

Some people get assigned to the control but get treated.

Reasons for Non-Compliance

- Person assigned to the treatment doesn't want it or take it.
- Person assigned to the treatment is unreachable:
  - Left the country / local area.
  - Doesn't respond to contacts.
  - Doesn't visit the website.
- Person who is supposed to give the treatment doesn't:
  - Doctor forgets to prescribe medicine.

Example: Diet

- Assign some people to eat the ‘Mediterranean diet’ and other to eat normally.

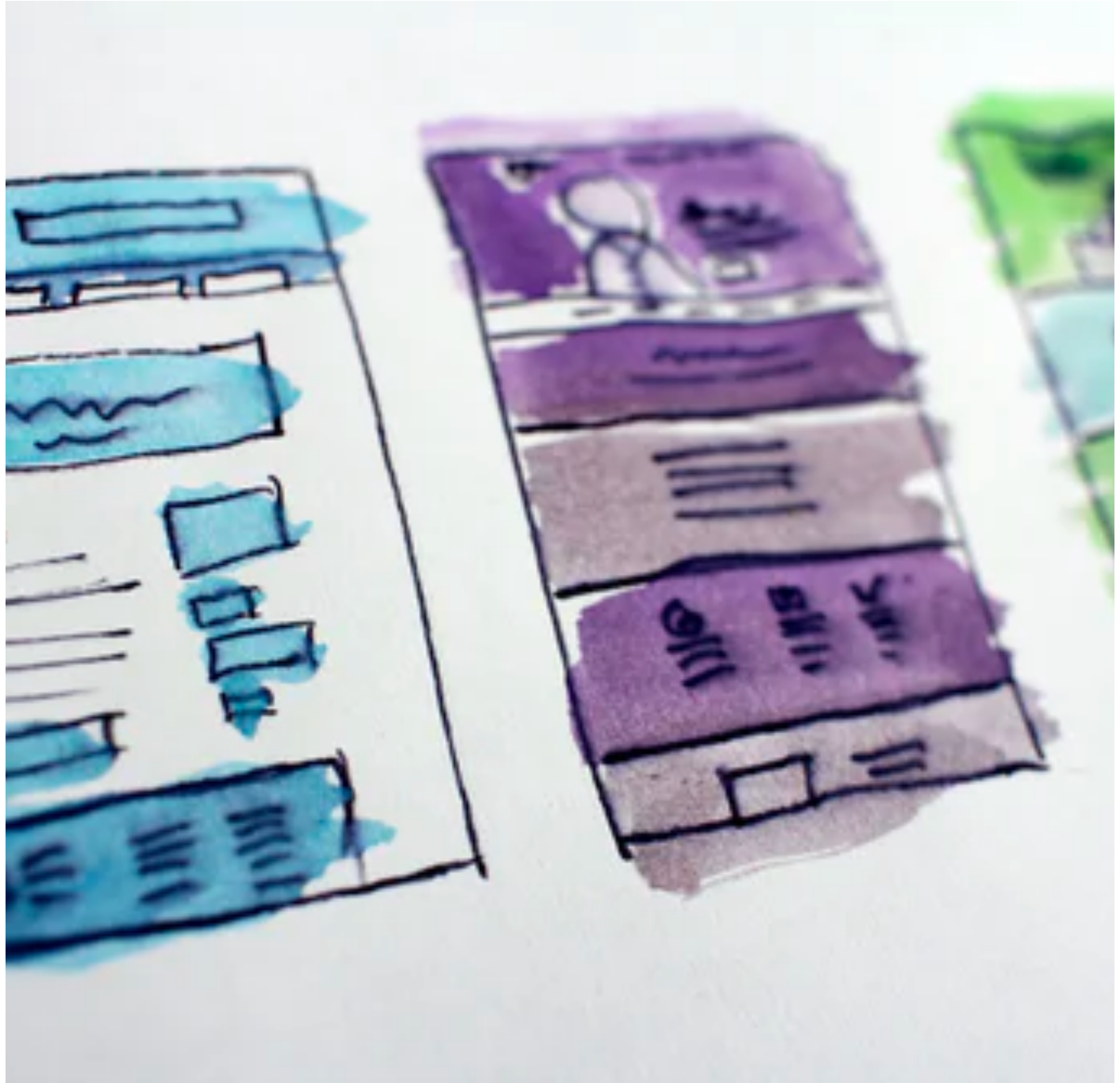
- Problem:

    - Just because people are told to eat the diet doesn’t mean they will.

    - No health effects of the diet if people don’t eat it.

Example: Website redesign

- Randomly assign users to redesign and see how it affects purchases.
- Problem:
    - Some people won't visit your site in this period
    - Those who do not visit the site will not be affected by the redesign.



Example: Reminders

- Randomly send email reminders for people to check their credit card statement.
- Problem:
  - Spam filter captures some emails and people don't see them.
  - People are not actually reminded if they don't see the email.

Many ways to define ‘treatment’ compliance.

- Do you see the ‘subject’ of the email. Maybe that has an effect.
- Do you click on the email?
- Do you click on the link in the email?
- Interpretation varies by which compliance variable we pick.

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Two Types of Effects of Interest

Intent to Treat (ITT)

- The causal effect of being **assigned** to the treatment group.
- Mixes people who are treated with those who are not treated but were assigned to treatment.
- Often this is a business relevant parameter. When launching a policy, there is usually some non-compliance.

Complier Average Causal Effect (CACE)

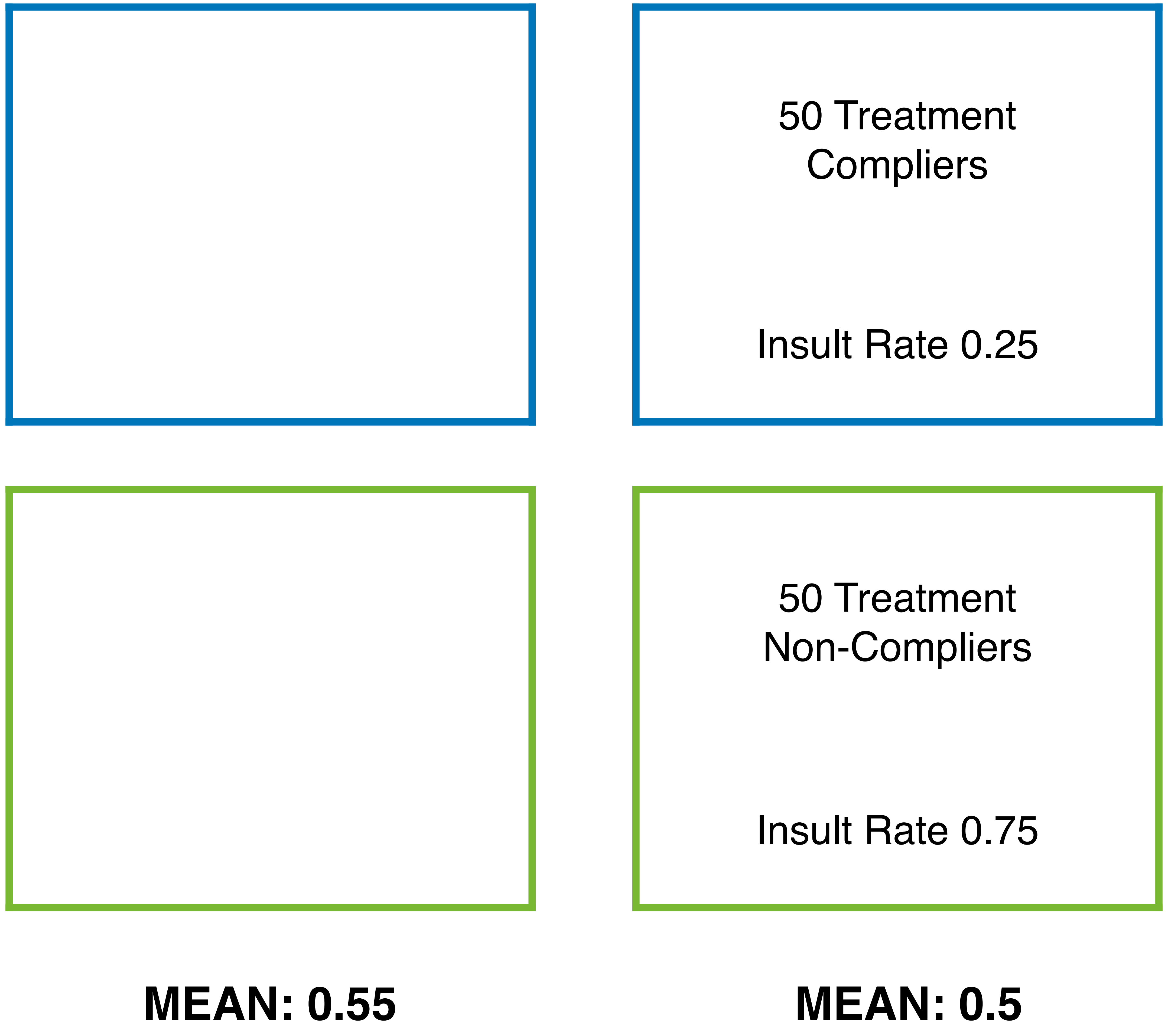
- Effect of the treatment on those who were treated (compliers).
- Allows us to learn what the effect of the treatment is for the subset of people who take it.
- Useful for thinking about interventions that increase treatment rates.

Example:

- We are a multiplayer gaming company such as Valve.
- One of our problems is that some gamers are trolls and insult the other players. We would like to reduce the rate of insults.
- We consider adding an in-game notification alert to gamers threatening to ban them if they continue to insult players. We are interested in reducing the rate of insulting behavior.
- We run an RCT where 50% of people have a notification alert. However, not everyone clicks on the notification alert. This is an example of non-compliance.

What would we see.

- Let's say we have 100 users in the treatment group and 100 users in the control group.
- We can measure when someone clicks on the alert.
- For each person we observe the insult rate.
- But… for the control group, we don't know who would've clicked in the alert if in the treatment group.
- ITT = - .05 (Treatment mean minus control mean)



Randomization helps.

- Due to randomization, we know that (on average) 50% of people in the control would also be complier.

50 Control Compliers	50 Treatment Compliers Insult Rate 0.25
50 Control Non-Compliers	50 Treatment Non-Compliers Insult Rate 0.75
MEAN: 0.55	**MEAN: 0.5**

Randomization helps.

- Due to randomization, we know that (on average) 50% of people in the control would also be complier.
- We know that the insult rate should be the same for non-compliers regardless of treatment group. They are not affected.

50 Control Compliers	50 Treatment Compliers Insult Rate 0.25
50 Control Non-Compliers Insult Rate 0.75	50 Treatment Non-Compliers Insult Rate 0.75
MEAN: 0.55	**MEAN: 0.5**

Calculating the Complier Average Causal Effect

- Insult rate for Control = .5 * (Insult rate for control compliers) + .5 * .75. = .55
- (Insult rate for control compliers) = (.55 - .5*.75)/.5 = **.35**

50 Control Compliers Insult Rate 0.35	50 Treatment Compliers Insult Rate 0.25
50 Control Non-Compliers Insult Rate 0.75	50 Treatment Non-Compliers Insult Rate 0.75
MEAN: 0.55	**MEAN: 0.5**

Calculating the Complier Average Causal Effect

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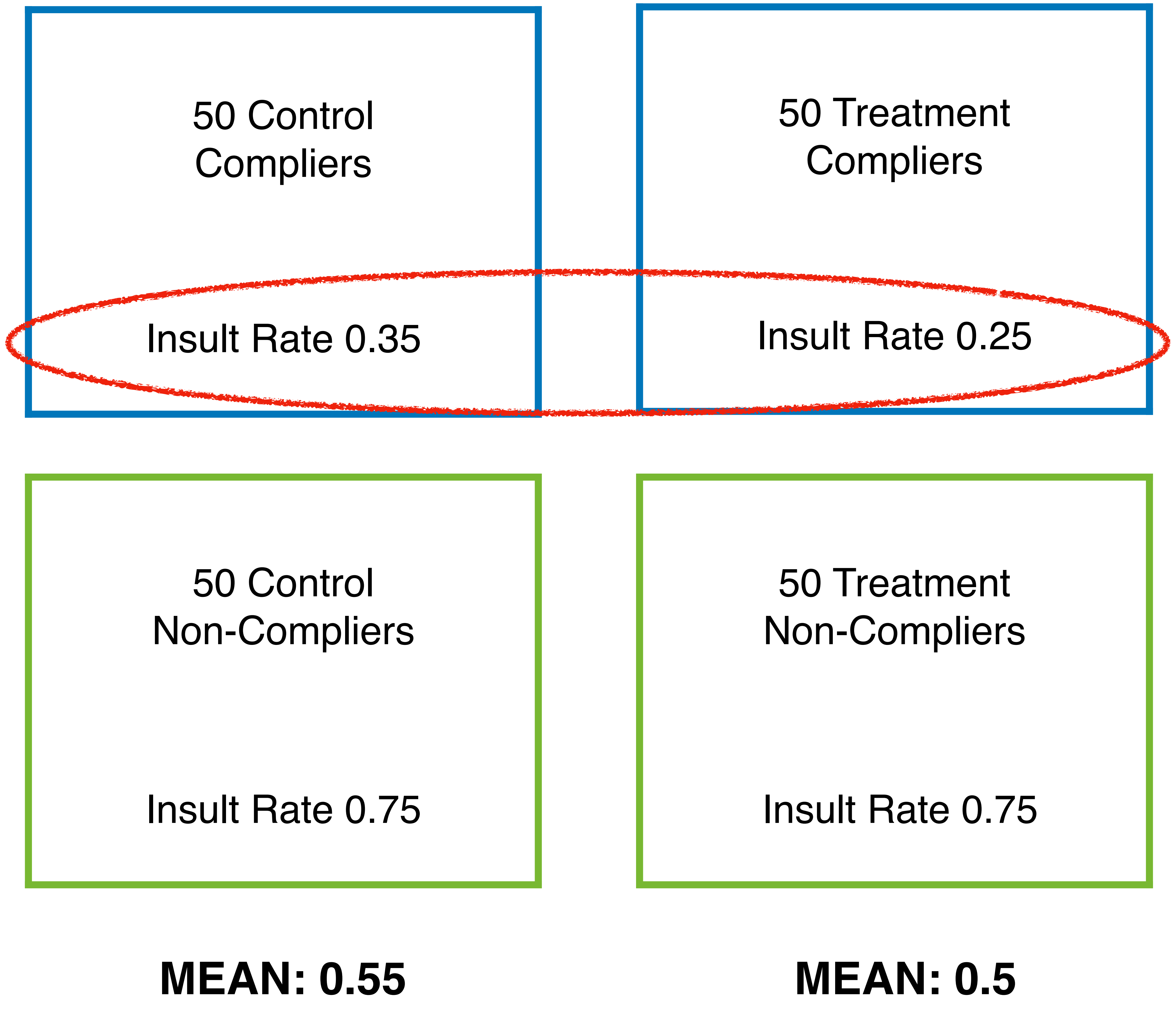
- (Insult rate for control compliers) = (.55 - .5*.75)/.5 = **.35**

- Complier Average Causal Effect = Insult rate for Treatment Compliers - Insult rate for Control Compliers
  = .25 - .35

- Insult rate falls by .1 due to reading the notification for those who comply.



Some Algebra

- α = share of treatment subjects treated.
- $\bar{Y}(1) - \bar{Y}(0) =$

$$\alpha(\bar{Y}_{Complier}(1) - \bar{Y}_{Complier}(0)) + (1 - \alpha)(\bar{Y}_{Non-Complier}(1) - \bar{Y}_{Non-Complier}(0))$$

- Assuming that being assigned to the treatment has NO effect on the non-compliers means the last term drops out.

$$\frac{\bar{Y}(1) - \bar{Y}(0)}{\alpha} = \bar{Y}_{Complier}(1) - \bar{Y}_{Complier}(0) = CACE$$

Let's Practice

- $CACE = \dfrac{\bar{Y}(1) - \bar{Y}(0)}{\alpha}$
- Average in Treatment = 80, Average in Control = 70, share-compliance = .2
- CACE = (80 - 70)/.2 = 50. Intuition, the entire difference is driven by 20% of the units.

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THE EFFECT OF CALLS ON VOTER TURNOUT

- Randomized field experiments with over 1 million subjects prior to the 1998 and 2002 U.S. elections.
- Here, a complier is someone who picks up the phone when called. (Again, these people exist in control group, too – even though they don’t actually get calls.)
- Outcome is voter turnout.

Treatment groups

- Control (no call)
- Treatment (call with a script)
- Placebo (call with a script about the red cross)

TREATMENT

Hi. This is (caller's name) calling from Vote '98, a nonpartisan group working with the League of Women Voters. We just wanted to remind you that elections are being held this Tuesday.

PLACEBO

Hi. This is (caller's name) calling on behalf of the American Red Cross to invite you to donate blood at an upcoming blood drive in your community. Each day volunteer blood donors are needed to support patients in Connecticut's hospitals. Your blood donation could save someone's life. Can a representative from your local blood drive call you to schedule an appointment?

Experimental results

TABLE 1
VOTER TURNOUT RATES BY EXPERIMENTAL GROUP

	Entire Sample		Those Called by Phone Bank	
Experimental Group	Turnout Rate	*n*	Turnout Rate	*n*
Control	51.5%	7,137		
Voter mobilization	51.1%	7,724	57.0%	5,271

Compliance Rate = 5271/7724 = 68%

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Compliance Rate = 5271/7724 = 68%

CACE = (0.511 - 0.515) / Compliance Rate

= -0.006

Why use a placebo?

- ITT / α can be noisy when α is small. SE(ITT/α) = SE(ITT)/α
- Placebo allows one to directly compare compliers.
- Makes sense to use when $\alpha < .5$

Placebo vs treatment compliance rate should be similar

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2089/3005 = 70%
5271/7724 = 68%

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CACE based on placebo vs treatment: 57% - 57.3% = -.03%

Downsides of a placebo

- Need to spend money for a placebo.
- Placebos require two assumptions:
  - Placebo has no causal effect on outcome.
    - E.g. giving blood does not interference with voting.
  - Compliers are the same types for placebo and for treatment.
    - E.g. people can’t tell the red cross is calling them.

Recap

1. Why not everyone might get the treatment.
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